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Article

Exploration on the innovation path of physical education teaching: The strategy of integrating personalized training and biosensor technology from the perspective of biomechanics

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Abstract: Background: PE is crucial for developing lifelong fitness habits among students. Traditional methods lack personalization and real-time feedback, limiting effectiveness. Biosensor technology, which can monitor various biomechanical parameters, offers a revolutionary approach to transform PE. It enables the provision of personalized training regimens based on each student's unique biomechanical characteristics, such as muscle force exertion patterns, joint kinematics, and body movement biomechanics. **Purpose:** The research aims to enhance and assess a new model of PE teaching that integrates personalized training with biosensor technology with a specific focus on how it impacts and interacts with the biomechanical and physiological aspects of students' physical performance. **Methods:** Data collection involves capturing HR, movement patterns, key biomechanical data and exertion levels during physical activities. The collected data are preprocessed using data cleaning and normalization techniques, ensuring the accuracy and reliability of this analysis. Feature extraction uses FFT to analyze the frequency domain characteristics of the physiological signals. The study proposes an ITSO-GRNN strategy aimed at developing PE teaching and personalized training. **Results:** The application of individual training together with biosensor technology contributes significantly and positively in terms of students' performance and involvement, resulting in better physical results and good evaluations. The ISTO-GRNN model outperforms all existing methods in terms of physical training (97.80%), assessing students' biomechanical and physiological states (99.62%), and efficiency of the PE teaching process (98.74%). In terms of performance metrics, it performs effectively with accuracy (98.70%), precision (96.50%), recall (90.42%), and F1-score (92.50%) showing teaching effectiveness and evaluation that are highly superior to those of the former models. **Conclusion:** The study highlights the potential for such innovations to not only improve physical outcomes but also promote lifelong fitness habits among students.

Keywords: biosensor; physical education; personalized training; intelligent tuna swarm optimization-driven gated recurrent neural network (ITSO-GRNN); biomechanics

1. Introduction

PE is crucial for student's physical fitness, enhancing cardiovascular endurance, strength, flexibility, and coordination through activities like team sports, swimming, running, and gymnastics while building confidence and appreciation for regular physical activity [1]. PE is not only improving physical health; it also empowers students with the skills and knowledge needed to incorporate physical activity into their daily lives. By engaging students in these activities, PE ensures the development of lifelong habits of physical fitness that contribute to overall health and well-being [2]. **Figure 1** demonstrates the PE teaching.

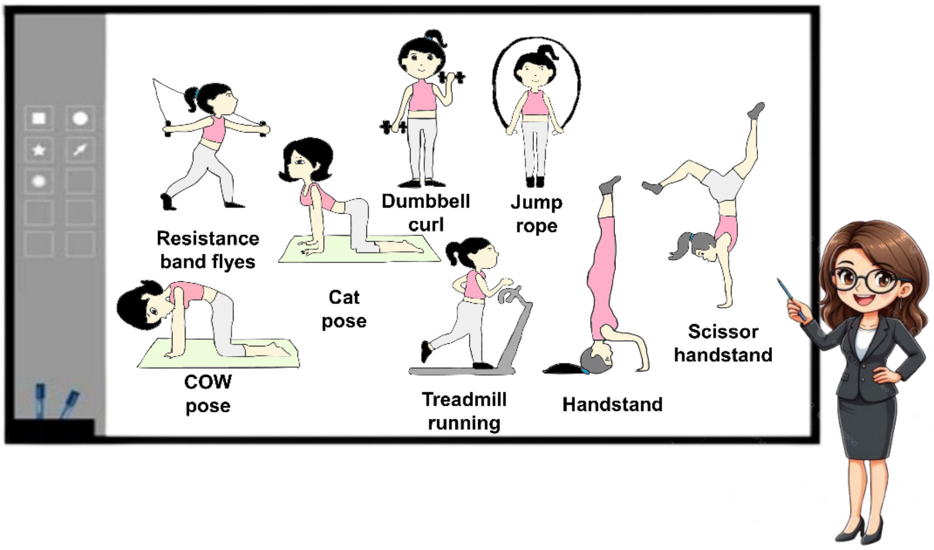

Figure 1. Physical education teaching.

1.1. Mental and emotional well-being through physical education (PE)

In addition to promoting physical fitness, PE plays a significant role in enhancing students' mental and emotional well-being. Engaging in exercise and aerobic activities has been demonstrated to alleviate stress, anxiety, and depression while improving one's mood, and cognitive ability [3]. In PE classes, for instance, there is an attempt to make students understand the relationship between physical activity and emotional well-being and how any physical activity helps them mentally [4]. PE lessons release endorphins in the brain, enhancing mood and well-being. Students not only improve their physical health but also learn to face challenges, overcome stress, and enhance their emotional well-being by participating in physical activities [5]. Within the method of overcoming physical activities as well as personal improvement, students learn vital competencies that help comprise feelings and enhance psychological fitness. **Figure 2** depicts the importance of PE teaching.

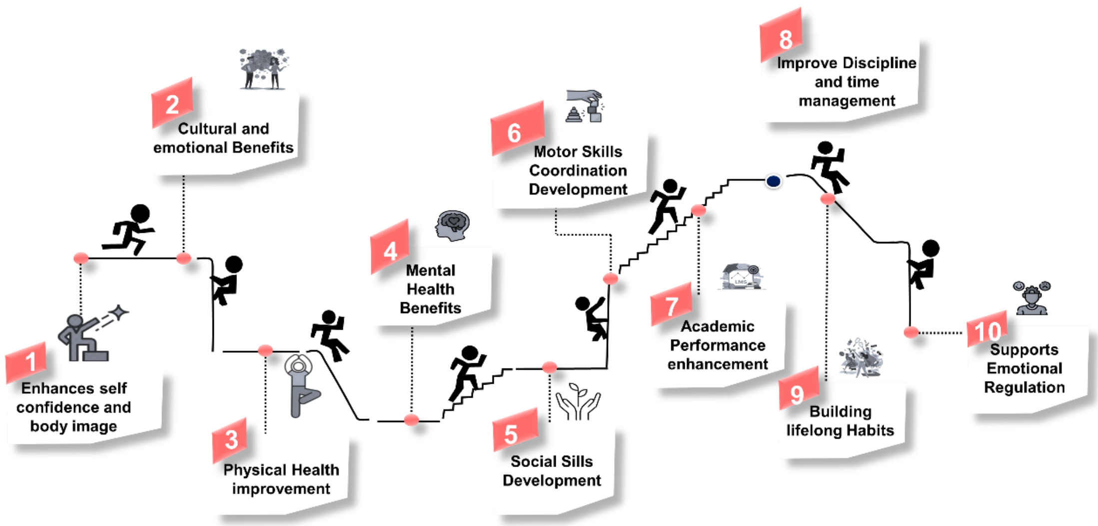

Figure 2. Significance of PE teaching.

1.2. Social development and lifelong learning in physical education (PE)

PE is vital for increasing physical well-being and developing social aspects, enhancing long-time engagement in physical activities. It presents a safe surroundings for youngsters to collect skills beneficial in various regions, contributing to a rounded schooling and fostering a healthy lifestyle [6]. In addition to learning sports, college students are worried in crew sports and institution games that allow them to collect critical social capabilities, including teamwork, communique, management skills, and empathy. The activities are structured to mimic actual spaces, so students get to learn how to work together, solve problems, and help each other in a particular environment [7]. Engaging in PE also encourages students to explore a variety of roles within team dynamics [8]. PE roles foster personal growth, teach cooperation and adaptability, and instill values like respect, equality, and sportsmanship, promoting well-rounded individuals beyond the playing field [9]. Physical education programs foster a lifelong appreciation for regular physical activity, instilling in children the desire and motivation to maintain active lifestyles and serving as an educational component [10]. PE programs equip students with knowledge and motivation to adopt and maintain an active, healthy lifestyle throughout adulthood, preparing them for school challenges and contributing to their long-term health and overall well-being.

Research objective: The study's goal is to create and evaluate a novel approach to PE instruction that combines biosensor technology with individualized training.

1.3. Research contribution

1) The study aims to create and evaluate a novel, PE teaching model that incorporates personalized training using biosensor technology.
2) Data collection involves capturing metrics like HR, movement patterns, and exertion levels.
3) Pre-processed data is utilized by the min-max normalization technique, and FFT was used for feature extraction.
4) The research proposes a new ITSO-GRNN strategy for personalized PE teaching and training.
5) Results show improved student performance and engagement, leading to improved physical outcomes.

Research organization: Section 2 contains the study's review of the literature, and Section 3 illustrates the methodology. Section 4 highlights the research's findings. Section 5 demonstrates the discussion, and the conclusion is established in Section 6.

2. Literature review

Table 1 provides a comprehensive overview of advanced research on PE teaching, detailing the literature, data, objectives, proposed methods, and limitations.

Table 1. Overview of various existing articles related to PE teaching.

REF	PUBLISHED YEAR	DATA	OBJECTIVE	PROPOSED METHOD	LIMITATION
[11]	2024	The dataset consists of online evaluation texts from male and female sports professional skill courses, as well as Expert skill instruction in basic and skilled sports.	The purpose is to establish an effective evaluation model for network teaching in sports professional technical courses to enhance education sustainability.	PSO-Attention-LSTM	Limited Learning Contexts
[12]	2024	The dataset used is the C-dance dataset contains folk dance training images.	The goal is to suggest novel training methods and enhance the folk-dance image recognition model's recognition impact.	DNN	Scalability to Other Dance Genres
[13]	2024	The dataset consists of parameters related to sports intensity and PE instruction within a sports-themed microgrid teaching model.	The purpose is to design and optimize a microgrid teaching model for improving practical sports instruction through knowledge graph inference.	Graph using a GNN modified with a SSA	Microgrid Teaching Model Scope
[14]	2024	The dataset includes physical fitness and activity data generated during college physical training sessions.	The purpose is to improve PE teaching and assessment through data mining to enhance the quality and management of PE instruction.	The proposed method is the DM approach for analyzing and managing PE classroom data, supported by a high-performance data storage and analysis framework.	Data privacy & scalability
[15]	2024	The dataset includes research on personalized teaching path recommendations and intelligent optimization algorithms, along with features of educators and teaching resources.	The purpose is to improve the quality of online PE teaching in Chinese colleges by creating a personalized path recommendation method.	MABPSO algorithm	MABPSO Model Scalability
[16]	2024	Data from fifteen institutions in the province of S.	To assess the influence of instructional quality in PE on students' core literacy and physical development.	TOPSIS	Limited Generalizability
[17]	2024	Athletes' performance and health data across various sports disciplines.	To enhance injury management in athletes by using AI to predict risks and improve recovery strategies.	AI-driven model utilizing data analytics and advanced ML techniques to predict injury risks and inform recovery strategies.	Injury Risk Variables
[18]	2024	Time series data for tennis instruction, utilized for learning the FCM.	To enhance tennis instruction through the integration of AI teaching assistants and intelligent teaching systems.	CS-FCM for automatic learning from time series data and a high-order FCM-based time series prediction framework	Complexity in Tennis Instruction

Table 1. (*Continued*).

REF	PUBLISHED YEAR	DATA	OBJECTIVE	PROPOSED METHOD	LIMITATION
[19]	2024	Survey data on college teachers' teaching ability and performance during training with the proposed optimization algorithm.	To enhance the impact of physical education teaching through digital learning and enhance the development of college students.	GA-BP-RF algorithm to improve node splitting in the RF algorithm for enhanced teaching optimization.	Teaching & Learning Variability
[20]	2024	Point cloud data obtained through LiDAR for virtual sports training.	Stimulate students' enthusiasm for sports training and reduce risks associated with professional training.	Use VR technology, Poisson Surface Reconstruction Algorithm, and OpenPose Human Posture Estimation Algorithm for immersive training.	Virtual Training Impact
[21]	2024	360-degree panoramic VR football teaching videos.	Develop the excellence of football training by integrating metaverse and AI technologies.	A 360-degree panoramic virtual reality football training video distribution approach based on K-means optimization.	Internet & Skill Retention
[22]	2024	363 Filipino educators' responses on ESD-related factors.	Explore factors influencing the integration of ESD in PE and Health.	PLS-SEM	ESD Integration Factors
[23]	2024	Input images with human body joint point location information.	Promote PE online courses and evaluate teaching effectiveness.	Human skeleton analysis, Pix2Pix algorithm, multi-scale feature fusion, and pixel-aligned implicit functions for 3D body model reconstruction.	Body Pose & Occlusion Handling
[24]	2024	500 college students from five universities in Jiangsu Province	To improve and optimize college students' cognitive capabilities through physical activity, considering self-efficacy and negative emotion as mediating and regulating factors.	Random sampling method with the use of physical activity, executive function, self-efficacy, and emotion scales.	Regional Participant Scope
[25]	2024	Using relatedness, competence, and autonomy, 478 middle school students encourage and inhibit certain behaviors.	To investigate the relationships between need satisfaction, frustration, and motivation in physical education and various combinations of students' assessments of instructional behaviors.	Two-step cluster analysis for teaching profiles and multivariate analysis of covariance for motivational outcomes.	Educational Level Applicability

Research gap

Despite the advancements in technology in PE, there is a lack of research on how personalized training and biosensor technology can be integrated to enhance the learning process. Traditional teaching methods neglect real-time biosensor feedback for individual student performance, suggesting a need for a balanced approach incorporating technology and considering physiological characteristics for effective learning.

3. Methodology

The research aims to generate a personalized PE teaching approach using biosensors to measure physiological changes in students. Wearable devices with advanced algorithms are used to measure students' responses to training, with a mixed methods sequential explanatory design. **Figure 3** denotes the overall research outline.

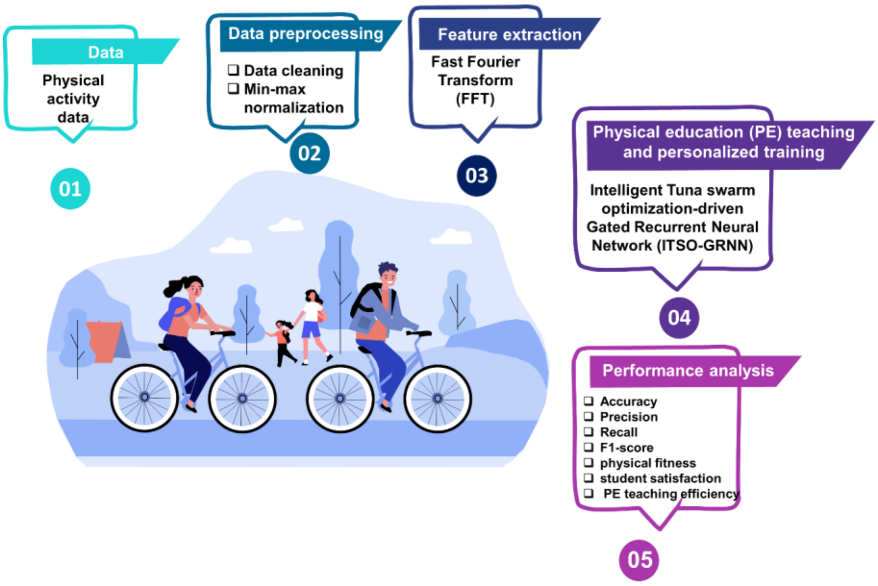

Figure 3. Research outline.

3.1. Data gathering

Table 2. Bio-sensor data to monitor physical activity.

Student ID	Bio-Sensors	Activity Type	Duration (min)	HR (bpm)	Movement Patterns	Exertion Level (1–10)
101	Smartwatch	Track & Field	40	130	Running, Sprinting	7
102	Smart Shirt, Smartwatch	PE Class	30	115	Stretching, Core Strength Exercises	5
103	Smartwatch	Basketball Practice	60	145	Jumping, Passing, Dribbling	8
104	Smartwatch	Fitness Training	45	122	Aerobic Exercises, Cycling	6
105	Smartwatch	General PE Activities	25	118	Walking, Stretching, Bodyweight Squats	4
106	Smartwatch	Soccer Practice	50	135	Running, Quick Changes in Direction	7
107	Smart Shirt, Smartwatch	Yoga and Flexibility	30	110	Yoga Poses, Balance Exercises	3

The data consists of information about students' physical activities and bio-sensor data, which include HR, movement patterns, exertion levels, and session details. The bio-sensors used for monitoring include smart watches for HR, blood pressure, calories burned, steps, and smart shirts to monitor muscle activity and flexibility. Every entry denotes the students' involvement in different physical activities, for instance, running, stretching, or engaging in the practice of sports. **Table 2** displays comprehensive data for each student, including exercise, duration of minutes, average heart rate (bpm), patterns of motion such as running, jumping, stretching, and self-reported effort levels on a scale of 1 to 10. This information aids in evaluating the time and severity of the student's physical activity, offering significant insights into their abilities and general fitness level. The combination of HR and movement data provides an in-depth analysis of students' exercise habits and effort levels, allowing for the optimization of personalized training plans.

3.2. Data cleaning using duplicate removal method

Data cleansing is the process of removing duplicate data from the data to maintain consistency and purity. It uses algorithms like Euclidian distance to detect near-duplicates and eliminate them to prevent overlap. This reduces the dependency on visual assessment, which causes errors in data analysis. Data cleansing helps to maintain data integrity and stability by suppressing duplicate entries from IoT network sensor readings.

i. Identifying Duplicates

The process involves comparing every entry to find duplicates through an exact match, which is represented by Equation (1).

$$Duplicate(,j) = \begin{cases} 1\ if\ xi = xj \\ 0\ otherwise \end{cases} \tag{1}$$

To achieve near matching, it is recommended to use a distance measure for different entries in Equation (2).

$$d(xixj) = \sqrt{\sum_{k=1}^{n} n(xik - xjk)} \tag{2}$$

The function duplicate (i, j) returns to 1 if the entries $xi$and xj are identical, and 0 otherwise. Here, $xi\ a$nd xj represent the individual data entries being compared. To assess near similarity, the Euclidean distance $d(xi, xj)$ is used, which calculates the distance between two entries. The variable n denotes the total number of dimensions or features in each entry, while xjk and xik are the values of the k-th feature for the entries xi and respectively.

ii. Removing duplicates

The process of removing duplicates Equation (3) involves keeping unique entries by retaining the first occurrence of each duplicate.

$$Cleaned\ Dataset = \{xi \mid xi\ is\ unique\ in\ D\} \tag{3}$$

In this context, the cleaned data is defined as the set of entries $\{xi \mid is\ unique\ in\ D\}$, where D represents the original dataset from which duplicates are removed.

iii. Verifying the Cleaning Procedure

The original and cleaned sensor data sizes were compared to determine the number of duplicates removed using the verification in Equation (4).

$$Reduction\ Ratio = \frac{\mid D \mid - \mid C \mid}{\mid D \mid} \times 100 \tag{4}$$

where $\mid D \mid$ is the original size and $\mid C \mid$ is the cleaned size. The data cleaning process involved removing duplicate entries from student activity data and ensuring unique records for analysis using Euclidean distance to identify near-matching entries in biosensor data for accuracy and integrity. Finally, the data cleaning process involved removing duplicate entries from the student activity data, ensuring that unique records remained for analysis. Euclidean distance is used to identify and eliminate near-matching entries in bio-sensor data, ensuring accuracy and integrity for each student's physical activity.

3.3. Data pre-processing using min-max normalization

The data cleaning campaign ensures accurate, complete, and fit data on student HRs, movement patterns, and exertion levels during physical activities, mitigating inconsistencies and avoiding skewed decisions by imputing missing values, detecting extreme values, and normalizing data distribution. The data is normalized to account for cross-participant variability, including HR and activity duration. The cleaning process converts categorical data like activity type into quantitative forms for efficient processing and modeling, ensuring high reliability in student physical interaction and fitness level insights. Min-mix normalization is a linear data modification technique that maintains connections among initial information by linearly moderating the data collection. An easy method of data corrects the position inside a predefined boundary using the help of min-max normalizing in Equation (5).

$$B' = \left(\frac{B - \min value\ of\ B}{\max value\ of\ B - \min value\ of\ B}\right) \times (C - D) + D \tag{5}$$

In B', one among the min-max standardized sets of information is contained. B represents the subsequently converted data if $[C, D]$ is the predefined perimeter and if B is the starting region. Min-max normalization ensures data consistency and precision in analyzing students' physical performance and fitness levels by ensuring variables like activity time fall within a predetermined range.

3.4. Feature extraction using fast fourier transform (FFT)

FFT is used to analyze frequency components of the data, allowing for the detection of periodic patterns and anomalies that can indicate underlying issues in the physical activities. It's a technique used to analyze running speed acceleration data by incorporating frequency components and translating data between rate and temporal domains. The Fourier transform changes the signal's foundation from time to frequency, as seen in Equation (6).

$$e(\omega) = \int_{-\infty}^{+\infty} e(s) f^{-j\omega s} ds \tag{6}$$

The signal $e(s)$ is subjected to an FFT, which separates into different frequencies. The FFT as described in Equation (7) allows users to analyze the frequency and amplitude of each frequency in the signal of this variable.

$$W(l) = \sum_{i=1}^{M} w(i) \omega_M^{(i-10(l-1)} \tag{7}$$

$\omega = f^{\frac{(-2\pi j)}{M}}$ represents the M^{th} root of unity. The frequency point count is M.The study extracted features like HR, movement patterns, and exertion levels to analyze students' physical performance and activity intensity, assessing the effects of various exercises on fitness levels. The result shows a clear correlation between activity type and exertion levels, highlighting the effectiveness of each activity.

3.5. Ntelligent tuna swarm optimization-driven gated recurrent neural network (ITSO-GRNN)

The proposed TSO-GRNN for PE and individual training integrates TSO technology with GRNN to improve the effectiveness of PE teaching and personal training. Optimizing movement recognition and performance prediction surpasses leveraging ITSO to enhance GRNN's customization capacity for individual learning patterns. The ITSO-GRNN approach aims to assist optimal teaching practices by developing data-driven solutions for individualized exercise prescriptions in real time.

3.5.1. Gated recurrent neural network (GRNN)

The GRNN is a technique used to analyze skeletal characteristics from biosensor data. It extracts key morphological features like bone shape, size, and orientation, and analyzes these through distance transformation. This method effectively models the skeletal structure, providing insights into body posture, movement patterns, and potential biomechanical anomalies. This personalized method enhances participation, identifies difficulty areas, and enables targeted teaching strategies. In **Figure 4**, the architecture is shown below.

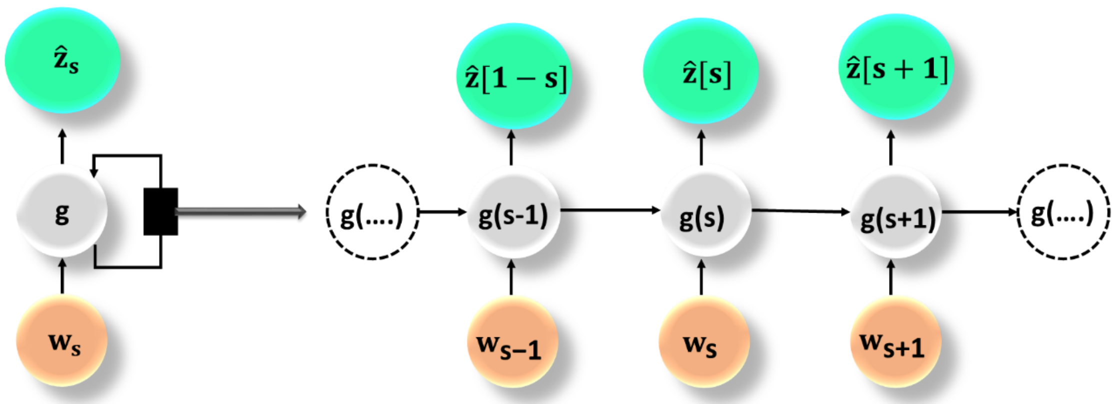

Figure 4. Architecture of GRNN.

GRNN ensures up-to-date and useful feedback, promoting improved understanding and student achievement. GRNNs perform well on data sequence processing tasks and employ GRNN to construct a concise depiction of the given input sequence $w[s]$. Function $e$performs the mapping in Equation (8).

$$g[s] = e(g[s-1], w[s];\ \Theta) \tag{8}$$

The following Equations (9)–(11) are satisfied by the neural computation when expanded and the sequence $w_s = \big[w[0], \dots, w[w_S - 1]\big], w[s];\ JQ^c$.

$$b[s] = X^S g[s-1] + V^S w[s] \tag{9}$$

$$g[s] = \phi(b[s]) \tag{10}$$

$$z[s] = \Psi(U^S g[s]) \tag{11}$$

where $X \in JQ^{mG \times mG}, V \in JQ^{c \times mG}, U \in JQ^{mG \times mP}$ are the influence matrix for hidden-hidden, hidden-output, and input-hidden associations, correspondingly, and $\phi(.)$ is a foundation purpose. S computation in a single Elmann GRNN module. A GRNN processes each sequence element individually, preserving its temporal order. The network uses both (a) and (b) to update its internal state $g[s] \in JQ^{mG}$after reading an element from the input sequence $w[s] \in JQ^c$ change of the most recent state $g[s-1]$. The resulting acyclic graph represents the process**.** Time unfolding is a process, and each node in an extended system has identical consideration as scattered clones. The network parameters$\Theta = [X, V, U]$ are typically learned through BPTT, a generalized version of standard backpropagation. Through the development process, the GRNN is changed into multiple layers and weight matrices to implement gradient-based optimization. In actual use, TBPTT (τ_a, τ_e) is employed, which executes BPTT for τ_a timesteps every τ_e processes an input window of length nT one timestep at a time. Setting τ_a to b extremely low integer of consequence in reduced performance.

3.5.2. Intelligent tuna swarm optimization (ITSO)

The ITSO is a modern optimization technique based on the dexterous foraging characteristic of tuna fish. It modifies the level of improvement in extracted features of the student data, allowing the model to understand and classify a wider array of features. ITSO enhances model efficiency by employing spiral and parabolic foraging tactics, enhancing forecast accuracy and performance in challenging works by driving prey to shallow water regions.

i. Population Initialization

The ITSO approach creates a random swarm in the search space during the swarm initiation stage. Equation (12) contains the following mathematical formulae for initializing tuna individuals.

$$W_j^{int} = rand \times (va - ka) + lb = \begin{bmatrix} w_j^1 & w_j^2 & \cdots & w_j^i \end{bmatrix} \begin{cases} j = 1,2,\dots,MO \\ i = 1,2,\dots,Dim \end{cases} \tag{12}$$

where W_j^{int} is the j^{th} tuna, va, and ka are the upper and lower tuna exploration boundaries, and rand is a random variable with a uniform distribution between 0 and 1. Each individual (W_j^{int}) in the ITSO represents a potential TSO solution. Each tuna consists of a set of Dim-dimensional integers.

ii. Parabolic Foraging Strategy

Eels and herring are tuna's main dietary sources. Users continuously alter their swimming direction to avoid predators by using their speed advantage. Predators have a hard time catching them. The tuna swarm's superior agility allows them to collectively strike victims, using the target as a reference for subsequent hunts. Each tuna in the swarm follows the one before it during predation, forming a parabola around the victim as represented by Equations (13) and (14).

$$W_j^{s+1} \begin{cases} W_{best}^s + rand \times \left(W_{best}^s - W_j^s\right), if\ rand < 0.5 \\ SE \times o^2 \times W_j^s, if\ rand \geq 0.5 \end{cases} \tag{13}$$

$$o = \left(1 - \frac{s}{s_{max}}\right)^{(s/s_{max})} \tag{14}$$

where s_{max} denotes the maximum number of preset iterations and s indicates that the s^{th} iteration is executing at the moment. SE is a random number between 1 and −1.

iii. Spiral-Based Hunting Technique

The spiral foraging strategy is another successful cooperative foraging method in addition to the parabolic foraging strategy. Most tuna struggle to navigate their prey, but a few can direct a group of fish, leading nearby tuna to follow. The tuna swarm uses a spiral foraging strategy, communicating with the closest individuals or the best individuals to follow. However, the best individual can't always capture prey, so the tuna randomly chooses which swarm to follow. Equation (15) provides the mathematical formula for the spiral foraging technique.

$$W_j^{s+1} \begin{cases} \alpha_1 \times \left(W_{rand}^s + \tau \times \left|W_{rand}^s - W_j^s\right| \alpha_2 \times W_j^s\right), j = 1 \\ \alpha_1 \times \left(W_{rand}^s + \tau \times \left|W_{rand}^s - W_j^s\right| \alpha_2 \times W_{j-1}^s\right), j = 1,2,..,MO, if\ rand < \frac{s}{s_{max}} \\ \alpha_1 \times \left(W_{best}^s + \tau \times \left|W_{best}^s - W_j^s\right| \alpha_2 \times W_j^s\right), j = 1\ , if\ rand \geq \frac{s}{s_{max}} \\ \alpha_1 \times \left(W_{best}^s + \tau \times \left|W_{best}^s - W_j^s\right| \alpha_2 \times W_{j-1}^s\right), j = 1,2,..,MO \end{cases} \tag{15}$$

where the j^{th} tuna in the $s+1$ iteration is indicated by W_j^{s+1}. The best person is W_{best}^s. The reference point chosen at random from the tuna swarm is called W_{rand}^s. α_1 is the trend weight coefficient that controls the tuna individual swimming to the recommended person or randomly selected adjacent persons. To control the tuna swimming toward the person in front of it, the trend weight coefficientα_2 is utilized. The distance parameter τ regulates the distance between the actual and reference individuals, chosen randomly as the ideal individual, as illustrated in Equations (16)–(19).

$$\alpha_1 = b + (1-b) \times \frac{s}{s_{max}} \tag{16}$$

$$\alpha_2 = (1-b) - (1-b) \times \frac{s}{s_{max}} \tag{17}$$

$$\tau = f^{ak} \times cos(2\pi a) \tag{18}$$

$$k = f^3 cos\left(\left((s_{max} + 1/s) - 1\right)\pi\right) \tag{19}$$

where, constant to measure the degree of tuna following and b is a randomly selected integer uniformly distributed in the interval [0,1]. Algorithm 1 demonstrates the ITSO-GRNN.

Algorithm 1 Intelligent Tuna swarm optimization-driven Gated Recurrent Neural Network (ITSO-GRNN)

```
Initialize GRNN
Initialize GRNN with random weights: W = {X, V, U}
Initialize sequence input [w[0], ..., w[w_S − 1]]
Train GRNN
For each time step s from 1 to S:
b[s] = X^S g[s − 1] + V^S w[s]
g[s] = ϕ(b[s])
z[s] = Ψ(U^S g[s])
Update GRNN weights using BPTT
Initialize ITSO
Initialize tuna swarm positions: W_j^int = random values in search space
For each tuna j in the swarm:
Evaluate the fitness of each W_j^int using objective function
ITSO Optimization Process
For each iteration from 1 to s_max:
   For each tuna j in the swarm:
      If rand < 0.5:
:W_j^{s+1} = W_best^s + rand × (W_best^s − W_j^s)
      Else:
:W_j^{s+1}= W_j^s
ITSO Optimization Process
For each iteration from 1 to s_max:
   For each tuna j in the swarm:
      If rand <(s/s_max):
:W_j^{s+1}= α_1 × (W_rand^s + τ × |W_rand^s − W_j^s| α_2 × W_j^s)
      Else:
:W_j^{s+1} = αα_1 × (W_rand^s + τ × |W_rand^s − W_j^s| α_2 × W_j^s)
Update Parameters
Update the best solution W_best^s based on the fitness values
Adjust the tuna swarm's position according to the optimization strategies
Optimize GRNN with ITSO
Fine-tune the GRNN parameters using ITSO-optimized values to personalize learning.
Update GRNN's weights using the optimized parameters from ITSO.
Output Predictions
Use the optimized GRNN to provide personalized exercise prescriptions and performance predictions.
```

The ITSO and GRNN methods have improved feature extraction and prediction accuracy, utilizing foraging behavior strategies. GRNN addresses the complexity of sequential data, such as human sports movements and walking postures, providing high-level information about user context. This combination enhances movement recognition and performance forecasting, providing real-time solutions for systematized physical education and training.

4. Performance analysis

The study aims to create and evaluate a new PE teaching model that incorporates personalized training using biosensor technology using the Python platform and includes metrics, such as strength improvement, endurance enhancement, coordination enhancement, student engagement, and instructor feedback.

4.1. Experimental setup

Table 3 outlines the hardware and software specifications of an HP computer, optimized for high performance and efficiency. Key components include dual processors, RAM, a modern operating system, and relevant software tools.

Table 3. Experimental setup.

Component	Specification
Brand	HP
Primary Processor	Intel Core i9-12900
Secondary Processor	Intel Core i7-13700
Clock Speed	3.50 GHz
RAM	64 GB
Operating System	Windows 11 Home
Python Version	3.10.0
L3 Cache Size	16 MB

4.2. Strength improvement

Biosensors in PE enhance strength, HR stability, cardiovascular health, and exercise response by providing high-accuracy monitoring, personalized training programs, sustained activity, and ensuring optimal performance and fitness. **Table 4** and **Figure 5** show strength training results for Strength Enhancement, showing maximum strength output (78%), moderate muscle endurance (72%), 65% of maximum load lifted, and exertion efficiency, indicating room for improvement in lifting ability and energy utilization efficiency.

Table 4. Outcomes of strength improvement.

Metrics	Value s (%)
Strength Output	78
Muscle Endurance	72
Max Load Lifted	65
Exertion Efficiency	65

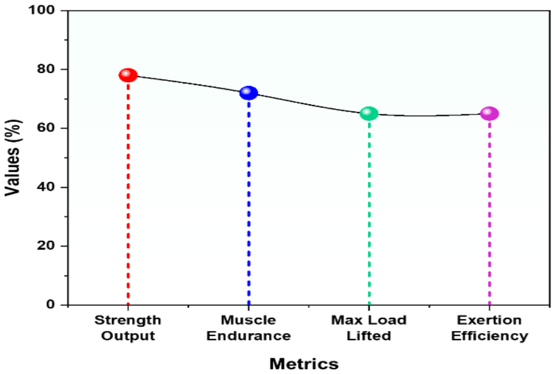

Figure 5. Graphical findings of strength enhancement.

4.3. Endurance enhancement

Biosensor improves the endurance of PE by enabling individualized training programs. This adaptive approach enhances force production, muscular endurance, and load capacity, reducing injury risks and equipping students with necessary fitness tools. **Table 5** illustrates significant measures for physical activity performance, with running time evaluating highest at 90%, and then HR stability (85%), sustained activity (80%), and recovery time (70%), demonstrating areas of and potential growth in physical fitness.

Table 5. Outcomes of endurance improvement.

Metrics	Values (%)
Running Time	90
HR Stability	85
Recovery Time	70
Sustained Activity	80

4.4. Coordination enhancement

Biosensor devices improve coordination in sports by assessing motion accuracy, speed, and response duration. Instructors can adjust load, improve skill development, and reduce injury risks by improving spatial understanding and control. **Table 6** displays coordination enhancement result, showing movement precision at 75%, motor coordination at 70%, agility completion at 68%, and reaction time at 60%. These scores indicate significant improvements in accuracy, adaptability to dynamic tasks, and potential for further improvement.

Table 6. Outcomes of coordination enhancement.

Metrics	Values (%)
Agility Completion	68
Movement Precision	75
Reaction Time	60
Motor Coordination	70

4.5. Student engagement

The PE curriculum success relies on student participation and biosensor-based personalized training to enhance fitness and interest levels. Data-based feedback encourages students to push limits, while coordination metrics measure movement precision and reaction time. **Table 7** and **Figure 6** show that student engagement is highest in feedback scores, reaching 85%, while other metrics show lower engagement levels, such as motivation and participation, suggesting a need to improve other aspects for a balanced engagement profile.

Table 7. Outcomes of student engagement.

Metrics	Values (%)
Class Participation	40
Motivation Levels	50
Activity Engagement	45
Feedback Score	85

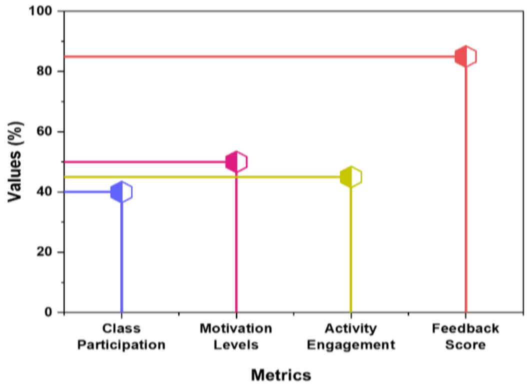

Figure 6. Graphical findings of student engagement.

4.6. Instructor feedback

Biosensor technology in primary health care improves teaching by providing real-time student performance data, enabling tailored instruction and timely training adjustments. Instructor feedback, monitoring improvement, personalized adjustments, and satisfaction measure effectiveness. **Table 8** shows that instructor feedback is effective in tracking student progress, with monitoring improvement scoring 92%, satisfaction at 90%, and personalized adjustments scoring 88%, indicating the ability to tailor instruction.

Table 8. Numerical outcomes of instructor feedback.

Metrics	Values (%)
Monitoring Improvement	92
Personalized Adjustments	88
Instructor Satisfaction	90

4.7. Comparative analysis

The study aims to enhance and assess a novel physical education method that integrates biosensor technology with personalized training. The proposed method compares with the existing methods, such as RNN [26], and MFEM-AI [27]. **Tables 9** and **10** demonstrate the overall numerical findings of ISTO-GRNN which outperforms RNN and MFEM-AI in all metrics, demonstrating greater effectiveness in enhancing physical education, with higher accuracy (98.70%), precision, recall, F1-score, and student satisfaction.

Table 9. Numerical findings of model performance.

Metric	Values (%)	
	RNN [26]	ISTO-GRNN [Proposed]
Accuracy	95.68	98.70
precision	94.52	96.50
Recall	85.59	90.42
F1-score	88.56	92.50

Table 10. Performance indicators.

Metrics	Values (%)	
	MFEM-AI [27]	**ISTO-GRNN [Proposed]**
Physical fitness	94.3	97.80
Student Satisfaction	91.9	99.62
PE Teaching efficiency	96	98.74

i. Accuracy

In PE teaching, accuracy refers to the proportion of correct predictions to total assessments made, reflecting overall teaching effectiveness. The ISTO-GRNN model achieves a higher accuracy (98.70%) compared to the RNN model (95.68%).

ii. Precision

The percentage of accurately recognized successful activities, out of all actions designated as successful is a measure of precision in physical education instruction, indicating how well positive outcomes are targeted. ISTO-GRNN outperforms RNN (94.52%) with a precision of 96.50%.

iii. Recall

Recall in PE teaching is the proportion of correctly identified successful actions out of all actual successful actions, showing how well the teaching system captures all instances of success. The ISTO-GRNN model shows an improved recall (90.42%) compared to RNN's recall (85.59%).

iv. F1-score

It is a teaching effectiveness information that combines both precision and recall, precisely evaluating students' abilities and motions. The ISTO-GRNN model demonstrated a higher f1-score rate (92.50%) compared to the RNN model's recall (88.56%). **Figure 7** displays the overall graphical outcomes of accuracy, recall, f1-score, and precision.

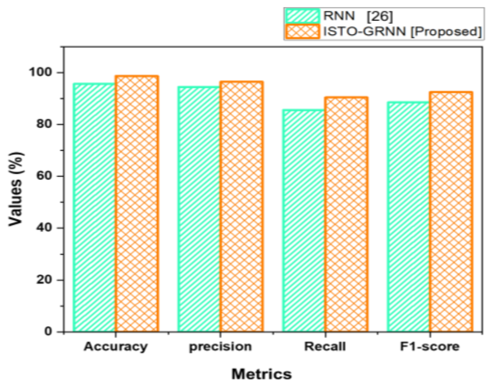

Figure 7. Graphical findings of performance metrics.

v. Physical fitness

Physical fitness in PE teaching refers to students' overall physical health and performance improvements, such as strength, endurance, and flexibility, resulting from the teaching program. The ISTO-GRNN model achieves a higher level of physical fitness (97.80%) compared to the MFEM-AI model (94.3%).

vi. Student satisfaction

Student satisfaction in PE education is a measure of students' contentment and engagement with the teaching methods, curriculum, and their learning experience in PE classes. ISTO-GRNN significantly outperforms MFEM-AI in student satisfaction, achieving 99.62% compared to MFEM-AI (91.9%).

vii. PE teaching efficiency

PE teaching efficiency evaluates how effectively educational methods and strategies contribute to students' physical development, focusing on the balance between time spent and progress achieved. The ISTO-GRNN model demonstrated higher outcomes of PE teaching efficiency (98.74%) compared to the MFEM-AI model96%. **Figure 8** displays the overall graphical outcomes of physical fitness, student satisfaction, and PE teaching efficiency.

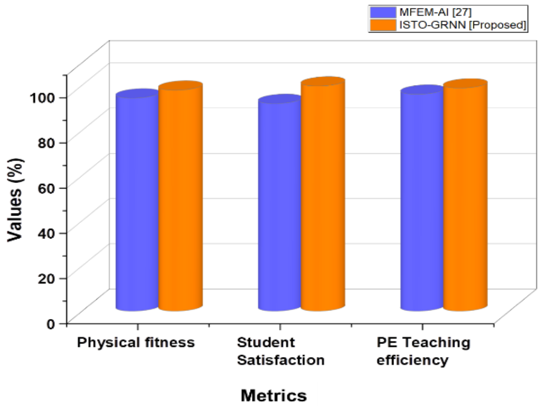

Figure 8. Graphical outcomes of performance indicators.

4.8. Discussion

To create and evaluate a novel approach to physical education instruction that combines biosensor technology with individualized training, the RNN [26] method in physical education faces challenges like computational complexity, vanishing gradient problems, multimodal input integration, resource requirements, and learning long-term dependencies in sequential data. The MFEM-AI [27] faces challenges, such as data input, biases, and modification of parameters. Essential problems with implementation, such as a lack of supplies and reliability, influence its practical usability. It should investigate its dynamic flexibility and applicability over time, as well as conduct longitudinal studies to determine the long-term effects of PETCU assessments. To promote interest in physical education, the model can be applied as an application for smartphones. The ITSO-GRNN enhances physical education teaching by improving movement evaluation, performance forecasting, and motor capability evaluation. It uses intelligent swarm optimization to provide immediate insight. This permits personalized training strategies that are adapted to each individual's demands. The methodology contributes to more accurate and successful physical education outputs.

5. Conclusion

Personalized training and biosensor technologies in PE coaching provide revolutionary and powerful mastering methods. By analyzing biosensor records on individual's physical activity and overall performance, training courses can be tailored to individual needs, improving health and participation. Despite challenges in widespread implementation, these equipment promote an agile approach, making them a crucial line of growth and research in PE. ISTO-GRNN model accomplished splendid results throughout all metrics, which includes bodily fitness (97.80%), student satisfaction (99.62%), and PE coaching efficiency (ninety eight.74%). In phrases of performance metrics, it additionally outperformed with accuracy (98.70%), precision (96.50%), consider (90.42%), and F1-rating (92.50%), demonstrating full-size upgrades in teaching effectiveness and assessment compared to previous models.

Drawbacks and future scope: The integration of personalized education and biosensor era in PE faces challenges like excessive implementation fees, records privateers, and specialized training. Future studies must improve sensor accuracy, reduce expenses, and discover lengthy-time period influences.

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Conflict of interest: The author declares no conflict of interest.

Nomenclature

PE	Physical Education
HR	Heart Rate
FFT	Fast Fourier Transform
ITSO-GRNN	Intelligent Tuna Swarm Optimization-driven Gated Recurrent Neural Network
AI	Artificial Intelligence
DNN	Deep Neural Network
GNN	Graph Neural Network
SSA	Salp Swarm Algorithm
DM	Data Mining
MABPSO	Multi-Agent-Based Particle Swarm Optimization
TOPISS	Technique for Order Preference by Similarity to Ideal Solution
PSO-Attention-LSTM	Particle Swarm Optimization algorithm - Attention-Long Short-Term Memory network
FCM	Fuzzy Cognitive Map
GA-BP-RF	Genetic Algorithm-Back Propagation-Random Forest
VR	Virtual Reality
LiDAR	Light Detection and Ranging
PLS-SEM	Partial Least Squares Structural Equation Modeling
Pix2Pix	Pix2Pix algorithm
3D	Three-Dimensional
PLS-SEM	Partial Least Squares Structural Equation Modeling
360-degree VR	360-degree Virtual Reality
ESD	Education for Sustainable Development
K-means	K-means clustering algorithm
IoT	Internet of things
ML	machine learning

TBPTT	Truncated Backpropagation Through Time
BPTT	Backpropagation Through Time
MFEM-AI	Multi-feature Fuzzy Evaluation Model based on Artificial Intelligence
RNN	Recurrent neural network
LiDAR	Light Detection and Ranging

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